Indonesian Journal of Electrical Engineering and Computer Science
Vol. 33, No. 2, February 2024, pp. 707~714
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v33.i2.pp707-714

Development of deep reinforcement learning for maximum power point tracking of photovoltaic systems

Thi Thom Hoang, Thi Huong Le
Department of Electrical and Electronic Engineering, Nha Trang University, Nha Trang, Vietnam

Article Info

Article history:

Received Sep 6, 2023
Revised Nov 16, 2023
Accepted Nov 27, 2023

Keywords:

Deep deterministic policy gradient
Deep reinforcement learning
Maximum power point tracking
Partial shading condition
Photovoltaic

ABSTRACT

The use of renewable energy systems, specifically photovoltaic (PV) systems (PVs) that convert solar energy into electricity, has become a popular solution to address global environmental concerns by reducing the utilization of non-renewable energy sources, which contribute to pollution. Efforts to increase the power transfer effectiveness of PV systems include the advancement of controllers for maximizing power point tracking (MPPT). These controllers guarantee optimal system operation at the maximum power point (MPP) in diverse environmental conditions. The paper proposes an improved deep reinforcement learning (DRL) method, namely deep deterministic policy gradient (DDPG), to capture the MPP in PV systems, particularly when dealing with partial shading conditions (PSCs). Unlike reinforcement learning methods that only work with discrete state and action spaces, the proposed DDPG method can handle continuous action state spaces. Feasibility analysis is conducted using MATLAB/Simulink simulations, and the findings demonstrate the efficiency and superior performance of the suggested solutions, highlighting their potential for future use.

Corresponding Author:

Thi Thom Hoang
Department of Electrical and Electronic Engineering, Nha Trang University
Nha Trang, Vietnam
Email: thomht@ntu.edu.vn

1. INTRODUCTION

The demand for energy has been steadily growing and is expected to increase substantially in the future [1]. In order to mitigate the consumption of carbon-based fuels and reduce pollution, there has been a rapid increase in the adoption of green energy sources. Solar energy, along with wind power, is widely utilized and has made a significant contribution to the global energy industry [2]. The decreasing cost and growing awareness of climate-altering emissions have led to the construction of numerous photovoltaic (PV) systems, especially in regions with abundant solar resources.

In addition to enhancing the manufacturing procedure of PV modules and energy converter units to improve system performance, it is crucial to increase the operating efficiency by employing an efficient controller for maximizing power point tracking (MPPT) [3], [4]. These algorithms are utilized with Busk/Boost converters to ensure that the maximum power point (MPP) is attained in various environmental scenarios, including variations in light intensity and climate. Various methods for tracking the MPP were introduced in previous researches.

The traditional MPPT algorithms, such as perturbation and observation (P&O) [5] and incremental conductance (IC) [6], have been widely applied because of their straightforwardness and straightforward integration. Other conventional methods, including open circuit voltage (OV), incremental resistance (INR), and ripple correlation control (RCC), have also been summarized in reference [7]. The effectiveness of traditional approaches has been demonstrated under uniform light intensity conditions [8]. However, these methods have a significant disadvantage of getting stuck at local maxima, resulting in low conversion efficiency in complex environmental conditions, especially in partial shading conditions (PSCs). Additionally, employing a duty cycle with a substantial step size may induce oscillation around the optimum point, while using a small step size leads to long training times. To address these issues, an improved P&O-based method is introduced, which utilizes a duty cycle with a perturbed step size that adjusts based on the distance from the MPP [9]. The main advantage of duty cycle-based methods utilizing a small step size enhances their capacity to remove oscillation.

Rezk summarized a group of soft computing-based MPPT controllers, including fuzzy logic controller (FLC) [10], artificial neural networks (ANN) [11], and neuro fuzzy methods [12]. Other methods, such as evolutionary methods like genetic algorithms (GAs) [13], cuckoo search algorithm (CSA) [14], ant colony optimization (ACO) [15], bat-inspired optimization (BAT) [16], and swarm optimization algorithms [17], show promise in addressing non-linear problems and achieving the MPP irrespective of varying environmental scenarios. However, these methods have the drawback of requiring expensive microprocessors and demanding extensive knowledge of PV systems.

Recent studies have extensively addressed the challenge associated with tracking the MPPT control using reinforcement learning (RL), which has demonstrated efficient learning abilities through interaction with the environment based on pre-defined data [18]–[20]. RL has shown faster convergence speed and shorter training times compared to heuristic algorithms. While some studies have focused on applying RL to MPPT control, they suffer from the limitations of small discrete state environment, leading to long training times. To overcome this issue, certain studies have proposed a combination of RL with other methods or utilized multi-agent approaches [20]. However, the challenges posed by PSCs have not been fully addressed in the aforementioned studies. Machine learning has recently advanced by integrating RL with deep learning (DL), leading to a promising approach known as deep reinforcement learning (DRL). DRL has shown potential for tackling optimization problems with large continuous state environment [21].

After reviewing previous research and analyzing the effectiveness of RL, it has been observed that very few papers have applied the DRL technique to MPPT controllers. In this study, a variant of the DRL algorithm, namely deep deterministic policy gradient (DDPG), is introduced to track the MPP in order to enhance the operating efficiency and robustness of PVs. The suggested approach based on DDPG involves utilizing a neural network to approximate either a value function or a policy function, enabling effective management of continuous state and action spaces. Additionally, to evaluate the efficacy of the proposed strategies, two tests are undertaken, including one test with uniform lighting and the additional scenario involving partial shading.

2. PROBLEM DESCRIPTION

A PV cell typically consists of two semiconductor layers that conduct electrical energy from solar irradiance. It is essential to use a dependable solar model to replicate the characteristic of PV cells, in which the model using two diodes is more precise; however, the model with a single diode has a simpler structure and is easier to employ [22]. This study uses a single-diode model and its corresponding equivalent electrical diagram of a PV cell as depicted in Figure 1.

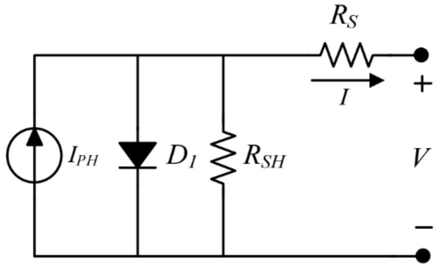


Figure 1. Modeling of a solar cell

The correlation between the PV cell's output current (I) and the photocurrent produced by light (IPH) can be calculated as follows:

$$I = I_{PH} - I_D - (\frac{V+I.R_S}{R_{SH}}) \quad (1)$$

where I_D represents the current following the diode D_1 that is expressed by (2):

$$I_D = I_s.[exp\left(\frac{V+I.R_S}{\sigma.V_{th}}\right) - 1] \quad (2)$$

where I_s is the diode current at the reverse saturation statue, σ is the ideal factor of diode D_1, and V_{th} refers to the thermal voltage of PV modules, as articulated by:

$$V_{th} = \delta.\frac{T}{q} \quad (3)$$

where δ represents the Boltzmann factor, T is the temperature of the p-n junction and q is the charge of an electron.

A PV array is made up of multiple modules that are interconnected in a series-parallel layout, represented as a matrix with NS rows and NP columns, as illustrated in Figure 2 [23]. The PV array is mathematically defined by:

$$I = N_P.[I_{PH} - I_D(I_p + 2)] - (\frac{V+\lambda.I.R_S}{\lambda.R_{SH}}) \quad (4)$$

where:

$$I_p = exp\left(\frac{V+\lambda.I.R_S}{V_{th}.N_S}\right) + exp\left(\frac{V+\lambda.I.R_S}{(N_P-1)V_{th}.N_S}\right) \quad (5)$$

$$\lambda = \frac{N_S}{N_P} \quad (6)$$

the power PPV provided by the panel can be computed by (7).

$$P_{pv} = V_{pv}.I_{pv} \quad (7)$$

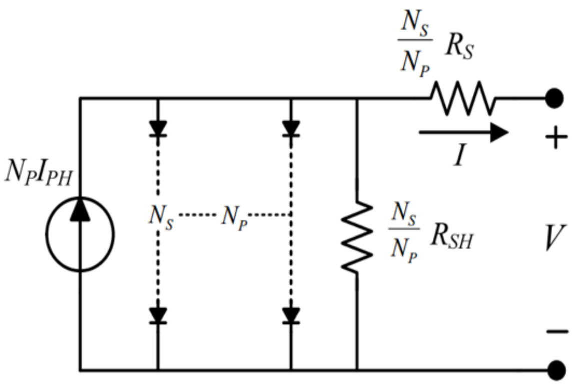


Figure 2. Modeling of a PV array

When PV modules are partially shaded, they can act as a load instead of an energy source. Therefore, a bypass diode is installed in parallel with the PV system to remove thermal stress and potential damage to the shaded modules [24]. However, this can result in multiple peaks on the PV characteristic curve, leading to up to 70% power loss if not properly addressed. Traditional MPPT control methods like P&O and IC will stop the tracking process as soon as the first peak is reached, making it impossible for these algorithms to accurately extract the overall MPP determined from the multiple peaks observed on the PV characteristic. Therefore, this paper proposes DRL-based MPPT controllers to track the global maxima under different weather conditions.

3. USING DDPG TO CONTROL MPPT
3.1. DDPG
DDPG, an evolved variant of RL, necessitates comprehension of RL it self. RL, a category of unsupervised machine learning, engages in interactions between an agent and its environment to deduce inputs and outputs. Recently, RL is being widely used in handling problems related to sequential decision-making. The objective of the RL algorithm is to gain insights into the optimal configuration or behavior of the system, allowing the agent to achieve the highest possible reward. Typically, RL problems are described by five components that define the control problem, including an agent, an environment, action spaces, state spaces, and a reward function.

DDPG algorithm proposed by Lillicrap *et al.* [25] uses a stochastic policy for exploration while estimating a simpler deterministic target policy for learning. DDPG employs an actor-critic architecture, incorporating two deep neural network models: the actor-network and the critic-network. These networks forecast the subsequent action for the present state and produce a temporal difference (TD) error signal at each step. Moreover, two sub-networks, target actor and target critic, facilitate the learning of the actor and critic by leveraging data from the memory buffer.

The actor-network has the output of $a(\mathrm{x}|\,\partial^{a})$, the critic network has the output of $C(x,\alpha|\partial^{C})$. Therefore, the target actor-network is known as $a'(x|\partial^{a'})$ and the target critic network is called as $C'(x,\alpha|\partial^{C'})$, where x represents the current statue of agents, α represents the value of an action, and ∂ is the corresponding weight of each network.

The loss value of critic network can be obtained by training its weights:

$$\mathrm{L} = \frac{1}{n}\sum_i (q_i - C(x_i,\alpha_i|\partial^{C}))^2 \tag{8}$$

where: $q_i = \omega_i + \beta C'\left(x_{i+1}, a'(\alpha_{i+1}\middle|C^{a'})\right)|\partial^{C'})$; β is the discount constant that is in the range of [0, 1]; ω_i is the reached cumulative reward after an action α_i is performed under the state x_i; n is the total training episodes. The actor-network is renewed by maximizing policy gradient.

$$\nabla_{\partial^a} P \approx \frac{1}{n}\sum_i \nabla_\alpha C(x,\alpha|\partial^{C})|_{x=x_i,\alpha=a(x_i)} \nabla_{\partial^a} a(a|\partial^{a})|_{x_i} \tag{9}$$

By training the the weights of the networks, the target actor-network and the target critic network are renewed as follows:

$$\partial^{a'} \leftarrow \mu\partial^{a} + (1-\mu)\partial^{a'} \tag{10}$$

$$\partial^{C'} \leftarrow \mu\partial^{C} + (1-\mu)\partial^{C'} \tag{11}$$

where μ is in the range of [0 1].

3.2. DDPG based MPPT controller
A PV system comprises essential components, including a PV array, a resistance load, an MPPT controller, and a buck/boost converter, all pivotal in MPP tracking. The MPPT controller adjusts the duty cycle (D) through a pulse width modulation (PWM) signal once the output of a PV array is linked to a buck/boost converter. this modification aims to control the voltage for optimal electrical power generation. The present study employs the DDPG algorithm for precise extraction of the global MPP in the PV system.

To implement a RL or DRL strategy for MPPT controller in PV systems, it is crucial to define a markov decision process (MDP) structure that characterizes the system's behavior. Typically, an MDP is defined as a sequence consisting of several components. The finite set of states, denoted as x, represents all possible operating points of the PV system. The finite set of actions, denoted as α refers to the perturbations applied to the duty cycle D. The transition function T defines how the system moves from one state to another based on the chosen action. The reward function ω determines the immediate reward received when an action is taken from the current state. It is important to note that the observation is composed of the combination of the voltage V_{pv}, the current I_{pv}, the duty cycle D , and its perturbation ΔD.

The reward function is used to balance the trade-off between the duration of the transient state t and the error in the duty cycle er. In mathematical terms, the reward function can be expressed as (12).

$$\omega = t_{old} - t_{new} + (er_{old} - er_{new}) * 10 \tag{12}$$

In (12), the factor of 10 indicates that the amplitude error holds greater significance as a minimum compared to the transient-state time. A MPPT controller using the optimization of DDPG algorithm whose diagram is shown in Figure 3 can be implemented by the following steps:
Step 1: the MPPT control algorithm begins by initializing the networks and the replay buffer RB
Initialize x = [0 0]; ep = 0: num_episodes
Step 2: during iteration, the agent chooses an action according to the current state and then proceeds to carry out that action within the environment.

$$D = \alpha = a(\mathrm{x}|\partial^{a})$$

Step 3: calculate the power: $P_{pv} = V_{pv}.I_{pv}$
Step 4: $Time$ is the time when the last P_{pv} starts to move
Step 5: $Error = |1 - \max(u)|$
Step 6: $Time_{old} = state[0]$; $Error_{old} = state[1]$
Step 7: calculate the cumulative reward according to (12)
Step 8: when the environment shifts to a new state, a reward is given based on the efficacy of the executed action: x $= [Time \quad Error]$
Step 9: the state, action, reward and future state are stored in the replay buffer
Step 10: update critic according to (8)
Step 11: update actor according to (9)
Step 12: update target networks according to (10) and (11).
The algorithm proceeds by updating the current state of the system. Eventually, the trained actor and critic networks, along with the replay buffer, are returned as the final outcome.

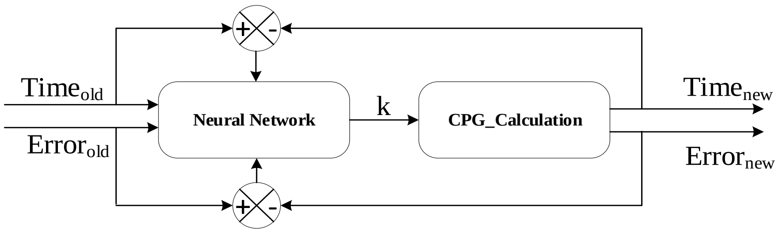


Figure 3. An illustration of the MPPT controller based on the DDPG algorithm

4. RESULTS AND DISCUSSION

In this paper, the proposed DDPG method is employed on a Canadian solar CS5P-220M PV module. It is noted that the tested PV system comprises three PV modules linked in series. To showcase the efficiency of the suggested approach, the PV system undergoes testing in two distinct scenarios: standard conditions and conditions involving PSCs.

4.1. Testing the proposed method for the photovoltaic system under uniform solar irradiation

Figure 4 illustrates the learning progress of the DDPG algorithm over 10,000 episodes. The rewards received by the agent at the end of each episode are represented by the blue lines, while the red lines depict the average rewards obtained from the beginning of the training process. The green line represents the estimated discounted long-term rewards at the start of each episode, specifically episode C_0.

In this subsection, the DDPG algorithm is introduced to track the true MPP of PVs, followed by a comparison of DDPG with DRL and traditional P&O methods to demonstrate the superiority of the proposed approach. The optimal controllers are applied to PVs under a uniform solar irradiation of 800 W/m2 and a fixed temperature of 25 °C. The results for the maximum power obtained are shown in Table 1.

Table 1 reveals that the DDPG-based MPPT controller demonstrates a close similarity to the theoretical value of maximum power, surpassing the performance of both the PSO-MPPT and P&O-MPPT controllers in terms of training time and efficiency. The DDPG-based controller achieves MPP tracking in just about 0.5 s, while both the DRL and P&O methods have similar training times of over 0.9 s. Furthermore, the DQN and DDPG methods exhibit power efficiencies of 98.72% and 99.04%, respectively, resulting in an increase of 1.74% and 2.06% compared to the P&O method. Figure 5 illustrate the response time of output power under standardized operating conditions when using an MPPT controller with the support of DRL and DDPG, respectively. It can be clearly seen from Figures 5(a) and (b) that the DDPG method gives a higher power efficiency than the DRL does.

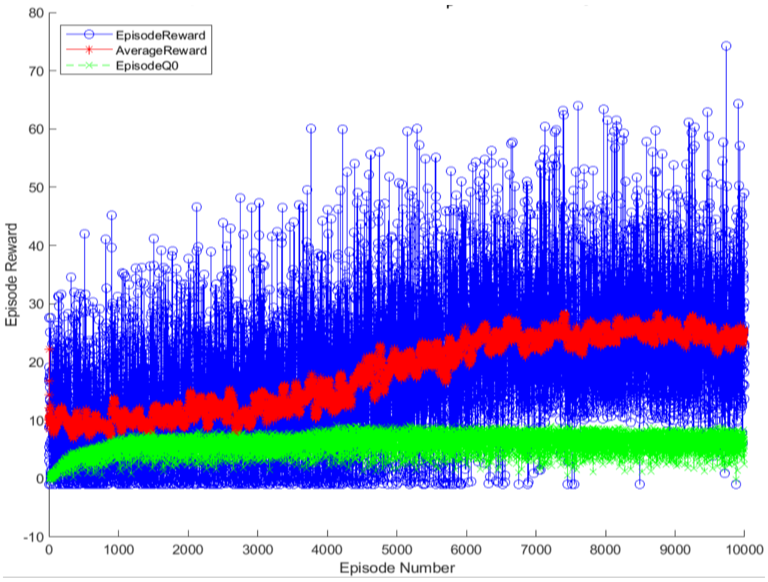


Figure 4. Training process of the DDPG-based MPPT controller

Table 1. The maximum power tracking results under uniform conditions

Methods	The theoretical value of PV (W/m^2)	The obtained maximum power (W/m^2)	The training time (s)	Power efficiency
P&O	532.71	516.62	0.95	96.98%
DRL	532.71	525.88	0.9	98.72%
DDPG	532.71	527.58	0.5	99.04%

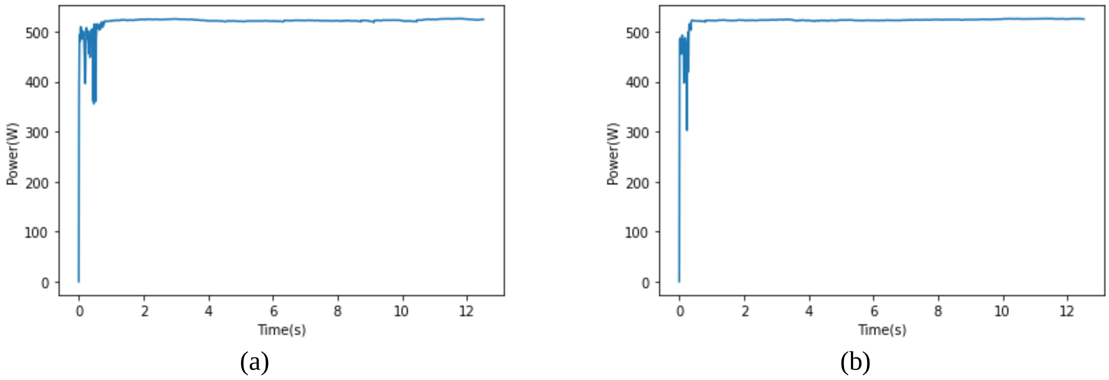


Figure 5. The response time of output power under a standardized operating condition (a) DRL and (b) DDPG

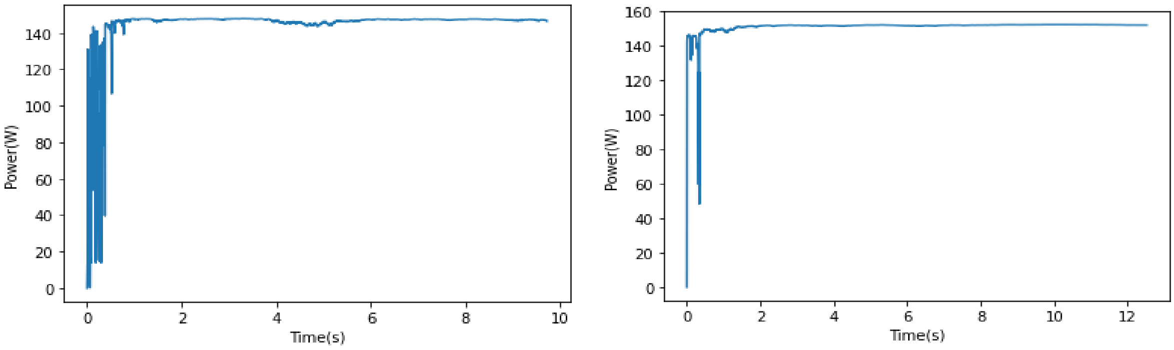
4.2. Testing the proposed method for the photovoltaic system under PSCs

In this subsection, various PSCs are employed to test and validate the proposed method. The methods are tested with two shaded PV modules, the irradiation values on the three modules are set as 800, 500, and 200 W/m2, respectively. To evaluate the response of the proposed MPPT controllers, the irradiation value of one PV module is decreased from 532.71 to 152.87 W/m2, compared to the standardized operating condition.

The simulation results are presented in Table 2, indicating that the DRL and DDPG methods can accurately reach the overal MPP with values of 147.89 W and 150.99 W, respectively. On the other hand, the perturb and observe (P&O) method is only capaciable of tracking the local MPP, leading to lower power efficiency. The efficiency of the P&O method is 22.67% lower than that of the DQN method and 24.7% lower than that of the DDPG method. Figure 6 illustrate the response time of the output power in the case of two shaded modules corresponding to the irradiation values of 500 W/m^2 and 200 W/m^2, respectively. In Figures 6(a) and (b) it can be observed that the DDPG algorithm achieves the highest power tracking efficiency with the shortest training time as compared to the DRL method.

Table 2. The maximum power tracking results under PSC

Methods	The theoretical value of PV (W/m^2)	The obtained maximum power (W/m^2)	Power efficiency
P&O	152.87	113.23	74.07%
DRL	152.87	147.89	96.74%
DDPG	152.87	150.99	98.77%



(a) (b)

Figure 6. The response time of output power in case of two shaded PV modules (a) DRL and (b) DDPG

5. CONCLUSION

The main aim of this investigation was to assess the efficacy of a recently developed RL technique known as DDPG in achieving MPPT in a PVs. The performance of this approach was compared with two other methods, DRL and P&O, with a focus on power tracking efficiency and convergence speed. All three methods successfully determined optimal duty cycles for a PWM generator, crucial for regulating the boost converter in a PV system, particularly under changing environmental conditions such as temperature and irradiation. Notably, the proposed DDPG algorithm exhibited the highest power tracking efficiency and the shortest training time. Additionally, the DDPG algorithm demonstrated accurate detection of the overal MPP under partial shading conditions, surpassing the capabilities of previous algorithms.

REFERENCES

[1] S. Leonori, M. Paschero, F. M. F. Mascioli, and A. Rizzi, "Optimization strategies for microgrid energy management systems by Genetic algorithms," *Applied Soft Computing Journal*, vol. 86, p. 105903, Jan. 2020, doi: 10.1016/j.asoc.2019.105903.
[2] K. Moharm, "State of the art in big data applications in microgrid: A review," *Advanced Engineering Informatics*, vol. 42, p. 100945, Oct. 2019, doi: 10.1016/j.aei.2019.100945.
[3] M. A. Danandeh and S. M. G. Mousavi, "Comparative and comprehensive review of maximum power point tracking methods for PV cells," *Renewable and Sustainable Energy Reviews*, vol. 82, pp. 2743–2767, Feb. 2018, doi: 10.1016/j.rser.2017.10.009.
[4] H. Islam *et al.*, "Performance evaluation of maximum power point tracking approaches and photovoltaic systems," *Energies*, vol. 11, no. 2, p. 365, Feb. 2018, doi: 10.3390/en11020365.
[5] M. Karabacak, "A new perturb and observe based higher order sliding mode MPPT control of wind turbines eliminating the rotor inertial effect," *Renewable Energy*, vol. 133, pp. 807–827, Apr. 2019, doi: 10.1016/j.renene.2018.10.079.
[6] S. Motahhir, A. E. Ghzizal, S. Sebti, and A. Derouich, "modeling of photovoltaic system with modified incremental conductance algorithm for fast changes of irradiance," *International Journal of Photoenergy*, vol. 2018, pp. 1–13, 2018, doi: 10.1155/2018/3286479.
[7] N. Karami, N. Moubayed, and R. Outbib, "General review and classification of different MPPT techniques," *Renewable and Sustainable Energy Reviews*, vol. 68, pp. 1–18, Feb. 2017, doi: 10.1016/j.rser.2016.09.132.
[8] A. Mohapatra, B. Nayak, P. Das, and K. B. Mohanty, "A review on MPPT techniques of PV system under partial shading condition," *Renewable and Sustainable Energy Reviews*, vol. 80, pp. 854–867, Dec. 2017, doi: 10.1016/j.rser.2017.05.083.
[9] J. Ahmed and Z. Salam, "An improved perturb and observe (P&O) maximum power point tracking (MPPT) algorithm for higher efficiency," *Applied Energy*, vol. 150, pp. 97–108, Jul. 2015, doi: 10.1016/j.apenergy.2015.04.006.
[10] S. D. Al-Majidi, M. F. Abbod, and H. S. Al-Raweshidy, "A novel maximum power point tracking technique based on fuzzy logic for photovoltaic systems," *International Journal of Hydrogen Energy*, vol. 43, no. 31, pp. 14158–14171, Aug. 2018, doi: 10.1016/j.ijhydene.2018.06.002.

[11] A. M. Kassem, “MPPT control design and performance improvements of a PV generator powered DC motor-pump system based on artificial neural networks,” *International Journal of Electrical Power and Energy Systems*, vol. 43, no. 1, pp. 90–98, Dec. 2012, doi: 10.1016/j.ijepes.2012.04.047.
[12] F. Belhachat and C. Larbes, “Global maximum power point tracking based on ANFIS approach for PV array configurations under partial shading conditions,” *Renewable and Sustainable Energy Reviews*, vol. 77, pp. 875–889, Sep. 2017, doi: 10.1016/j.rser.2017.02.056.
[13] Y. Shaiek, M. B. Smida, A. Sakly, and M. F. Mimouni, “Comparison between conventional methods and GA approach for maximum power point tracking of shaded solar PV generators,” *Solar Energy*, vol. 90, pp. 107–122, Apr. 2013, doi: 10.1016/j.solener.2013.01.005.
[14] J. Ahmed and Z. Salam, “A maximum power point tracking (MPPT) for PV system using cuckoo search with partial shading capability,” *Applied Energy*, vol. 119, pp. 118–130, Apr. 2014, doi: 10.1016/j.apenergy.2013.12.062.
[15] S. Titri, C. Larbes, K. Y. Toumi, and K. Benatchba, “A new MPPT controller based on the Ant colony optimization algorithm for Photovoltaic systems under partial shading conditions,” *Applied Soft Computing Journal*, vol. 58, pp. 465–479, Sep. 2017, doi: 10.1016/j.asoc.2017.05.017.
[16] K. Kaced, C. Larbes, N. Ramzan, M. Bounabi, and Z. E. Dahmane, “Bat algorithm based maximum power point tracking for photovoltaic system under partial shading conditions,” *Solar Energy*, vol. 158, pp. 490–503, Dec. 2017, doi: 10.1016/j.solener.2017.09.063.
[17] B. Yang *et al.*, “Novel bio-inspired memetic salp swarm algorithm and application to MPPT for PV systems considering partial shading condition,” *Journal of Cleaner Production*, vol. 215, pp. 1203–1222, Apr. 2019, doi: 10.1016/j.jclepro.2019.01.150.
[18] R. C. Hsu, C. T. Liu, W. Y. Chen, H. I. Hsieh, and H. L. Wang, “A reinforcement learning-based maximum power point tracking method for photovoltaic array,” *International Journal of Photoenergy*, vol. 2015, pp. 1–12, 2015, doi: 10.1155/2015/496401.
[19] X. Zhang *et al.*, “Memetic reinforcement learning based maximum power point tracking design for PV systems under partial shading condition,” *Energy*, vol. 174, pp. 1079–1090, May 2019, doi: 10.1016/j.energy.2019.03.053.
[20] M. Ding *et al.*, “Global maximum power point tracking of pv systems under partial shading condition: A transfer reinforcement learning approach,” *Applied Sciences (Switzerland)*, vol. 9, no. 13, p. 2769, Jul. 2019, doi: 10.3390/APP9132769.
[21] M. Lapan, *Deep Reinforcement Learning Hands-On. Apply modern RL methods, with deep Q-networks, value iteration, policy gradients, TRPO, AlphaGo zero and more*. Packt Publishing Ltd., 2018.
[22] R. B. A. Koad, A. F. Zobaa, and A. El-Shahat, “A novel MPPT algorithm based on particle swarm optimization for photovoltaic systems,” *IEEE Transactions on Sustainable Energy*, vol. 8, no. 2, pp. 468–476, Apr. 2017, doi: 10.1109/TSTE.2016.2606421.
[23] T. T. Hoang and T. H. Le, “Application of mutant particle swarm optimization for MPPT in photovoltaic system,” *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 19, no. 2, pp. 600–607, Aug. 2020, doi: 10.11591/ijeecs.v19.i2.pp600-607.
[24] M. Dhimish, “Assessing MPPT techniques on hot-spotted and partially shaded photovoltaic modules: Comprehensive review based on experimental data,” *IEEE Transactions on Electron Devices*, vol. 66, no. 3, pp. 1132–1144, Mar. 2019, doi: 10.1109/TED.2019.2894009.
[25] T. P. Lillicrap *et al.*, “Continuous control with deep reinforcement learning,” *arXiv preprint*, 2015, doi: 10.48550/arXiv.1509.0297.

BIOGRAPHIES OF AUTHORS

Thi Thom Hoang received B.E. degree in automatic control in 2006 from Hanoi University of Technology and Science, the M.E. degree in automation in 2012 from Le Quy Don University, and the Ph.D. degree in electrical engineering in 2018 from National Kaohsiung University of Science and Technology, Taiwan. She is currently an Associate Professor with Department of Electrical and Electronic Engineering, Nha Trang University. Her research interests include artificial intelligence and green power. She can be contacted at email: thomht@ntu.edu.vn.

Thi Huong Le received B.E. degree in electrical engineering in 2011 from Nha Trang University, and the M.E. degree in Electrical Engineering 2019 from Ho Chi Minh University City of Technology. She is currently a lecturer at Department of Electrical and Electronic Engineering, Nha Trang University. Her research interests include electrical machines and renewable power. She can be contacted at email: huonglt@ntu.edu.vn.